



Life Prediction Modeling of Lead-Acid Batteries in Stationary Backup Power Applications

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[←Home](#)

[←Agenda](#)





Technical Goal & Objective

Goal:

- ❑ To develop quantifiable end-of-life prediction capability for stationary power source systems in backup power applications to improve dependability and reliability in services.

Objective:

- ❑ To develop a practical and reliable life prediction tool for VRLA batteries used in energy storage backup power applications via advanced computer modeling to enable timely replacement of batteries while reducing inspection and maintenance costs.



End-of-Life Determination and Issues

- ☐ Prediction of the End-of-Life (EOL) of a stationary battery system in service is very difficult, expensive, and destructive to the system.
- ☐ Critical to establish system reliability, dependability, and warranty.
- ☐ Techniques to determine remaining discharge capacity are highly desired, especially without removing the system from service to perform a measurement.
- ☐ Can we functionally relate EOL to any easily measurable quantities?
- ☐ Can we functionally relate these measurements to quantities that are logically computable because of electrochemical phenomenology?
- ☐ Combination of some or all of above.



Critical Factors that Influence VRLA Battery Life

External Factors (Duty Cycle)

- ☐ Environment/Site Conditions
- ☐ Temperature
- ☐ Thermal Management
- ☐ RMS AC Ripple
- ☐ Discharge and Charge Regimes
- ☐ Discharge Frequency
- ☐ Depth of Discharge vs. Time
- ☐ Float Charge Voltage
- ☐ Float Current

Intrinsic Cell Characteristics

- ☐ Cell Design
- ☐ Battery Responses
- ☐ Battery Performance vs. Operating Temperature
- ☐ Discharge Capacity
- ☐ Cell Impedance
- ☐ Conductivity & Contact Resistance
- ☐ Grid Corrosion & Rate
- ☐ Recombinant Behavior & Water Loss

➔ Impacts from both standby and duty cycle modes need to be captured



(Traditional) Sequential Path to Battery Life Prediction

- ☐ **Gather readily available data**
- ☐ **Commence study to establish which phenomenological measures are most relevant**
- ☐ **Establish what data are desirable and prepare test plan**
- ☐ **Commence battery testing**
- ☐ **Commence analysis of available data**
 - ❖ **Computation of phenomenological measures**
 - ❖ **Development of suitable mathematical algorithm**
 - ❖ **Modeling and prediction**
- ☐ **Assess model performance and validate**

→ Time Consuming & Inefficient

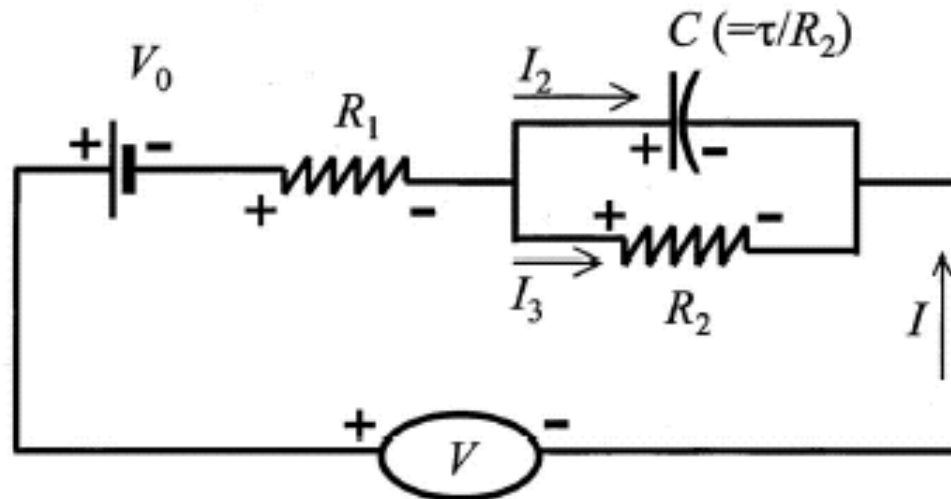


Our Approach -- Concurrent Path to EOL Prediction

- ❑ Development of suitable model and modeling capability based on current understanding
 - ❖ Use simple but practical equivalent circuit model approach to develop performance prediction capability
 - ❖ Use artificial neural network approach to develop adaptive life prediction capability over a wide range of conditions
- ❑ Collection of relevant data
 - ❖ Test protocols and test plan
- ❑ Prediction and validation
 - ❖ Criteria

Equivalent Circuit Model (ECM)

- ❑ A simple equivalent circuit model (ECM) can describe complicated behaviors and responses in an electrochemical system.
- ❑ Can provide some insightful phenomenological understanding of the system performance.
- ❑ A simple ECM is currently used in this work:





Artificial Neural Network (ANN): Motivation

- ❑ Data characterizing EOL phenomena can be extremely complex and the underlying mechanisms might not be completely understood or impossible to fully describe.**
- ❑ The simple equivalent circuit model may not be sufficient for complicated duty and service cycles such as those in the stationary applications, which might induce EOL mechanism change over a long service period and wide range of conditions.**
- ❑ Once trained, the adaptive capability of ANNs allows for the incorporation of new data to improve fidelity, which may come from previously unknown degradation mechanisms.**
- ❑ ANNs can provide functional relationships for use conditions that were not part of the initial training set. Interpolation between trained conditions and some limited extrapolation is possible.**

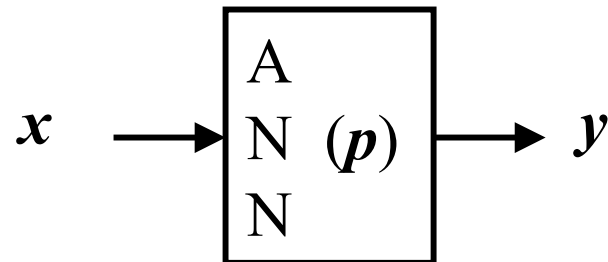
Artificial Neural Network: Fundamentals/Training

Given:

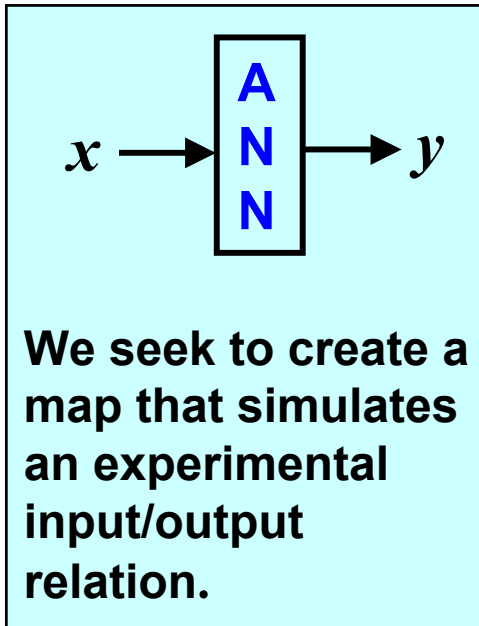
- Correct examples of input/output behavior (exemplars)

$$x_j, z_j, j = 1, \dots, n$$

- The artificial neural network (ANN) framework with parameters p



- We seek to train the ANN (optimize the parameters, p) to simulate the behavior of the exemplars.



This is accomplished through a learning process.

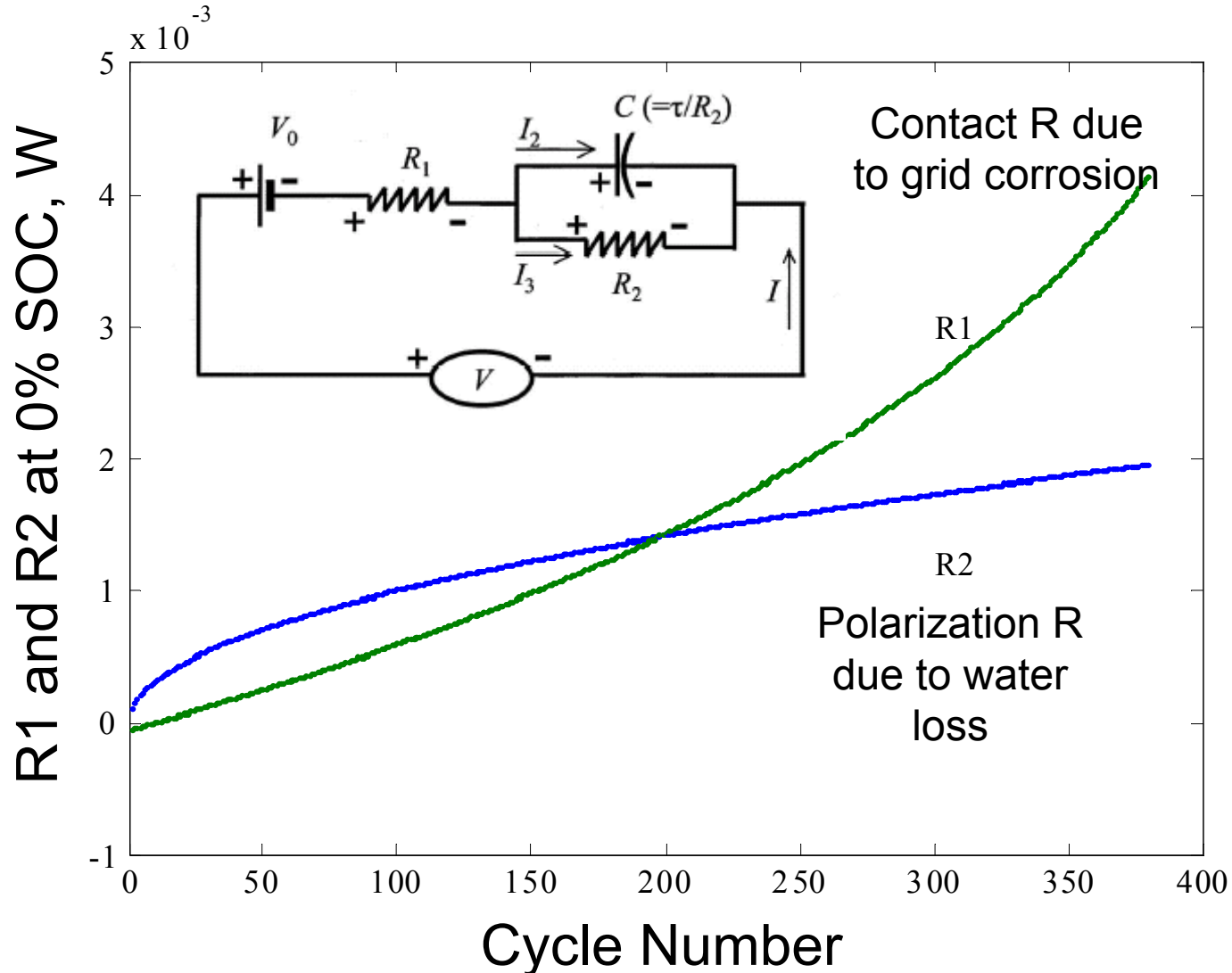


Artificial Neural Network: Modeling Approach

- ☐ Investigate the capacity loss as a function of discharge rate and temperature.
- ☐ Create individual ANN models at selected temperatures (20, 30, 40 and 50°C) and discharge rates (C/1 to C/3 in steps of 0.25).
- ☐ Models are splined together to create an overall model for each discharge rate and temperature condition.
- ☐ Interpolation and a limited amount of extrapolation was performed
- ☐ ANN model is shown to reflect the overall trend of the underlying data

ECM Approach:

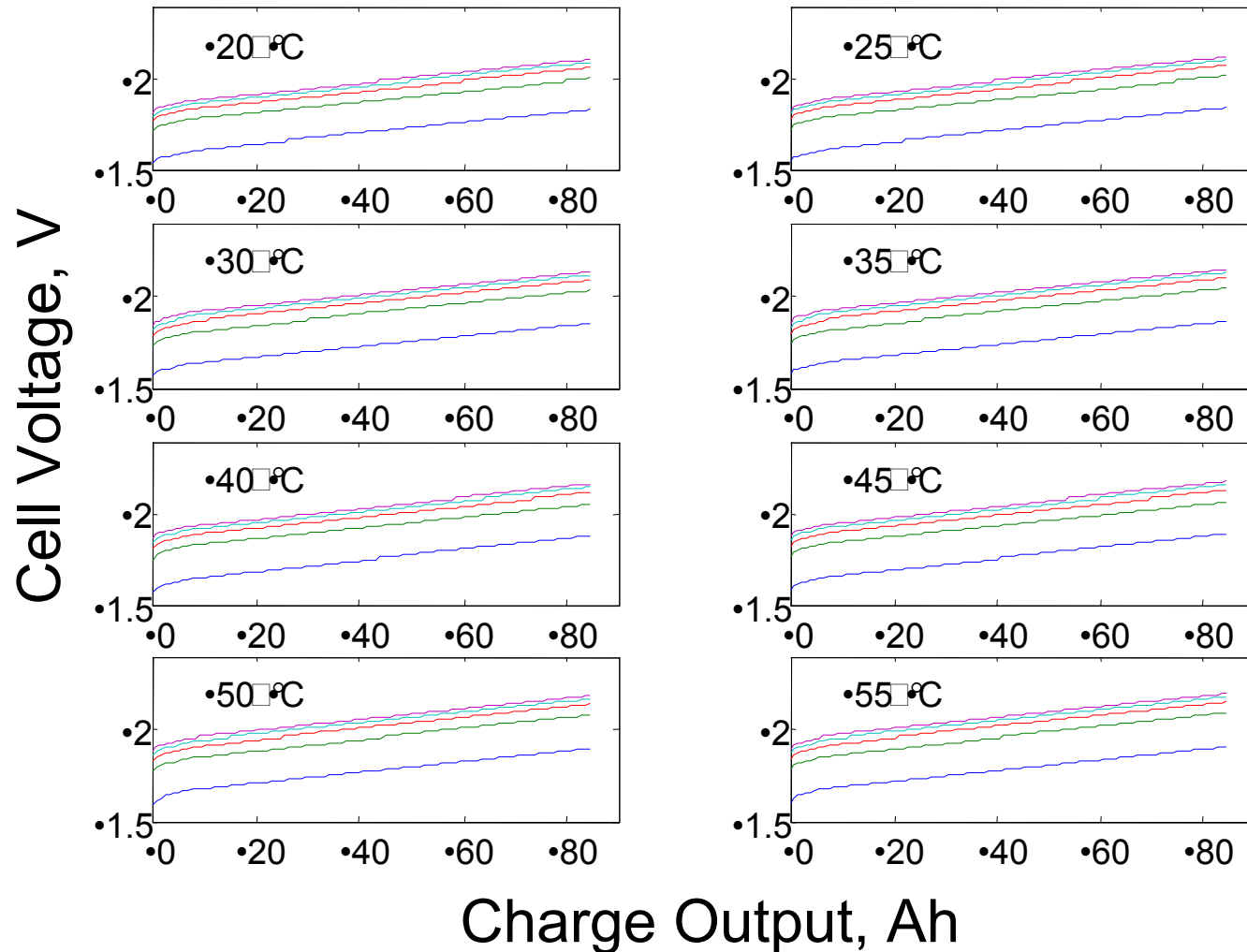
Cell Impedance Changes with Cycles





ECM Results:

Temperature Dependence of Discharge Cell Voltage

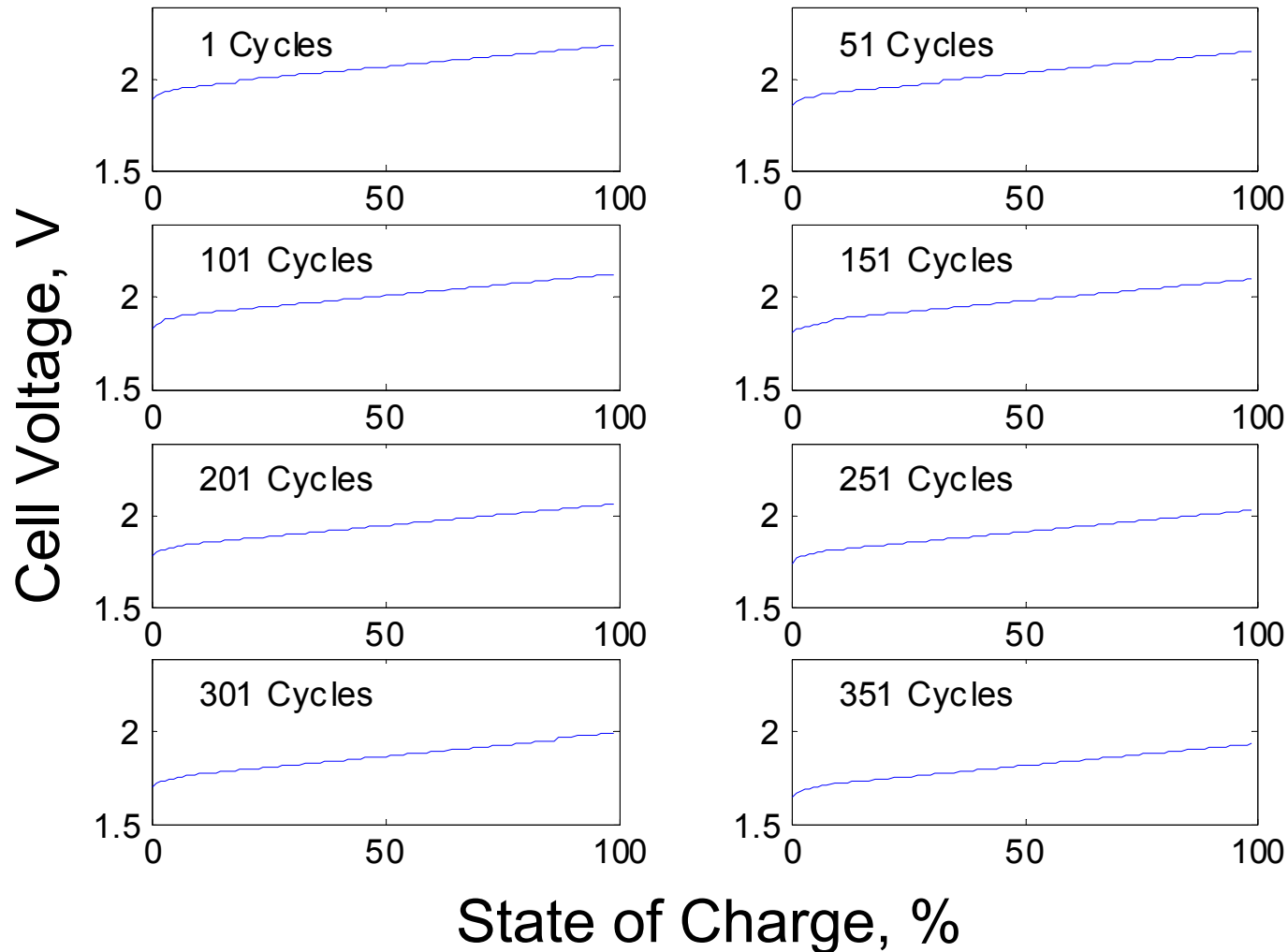




ECM Results:

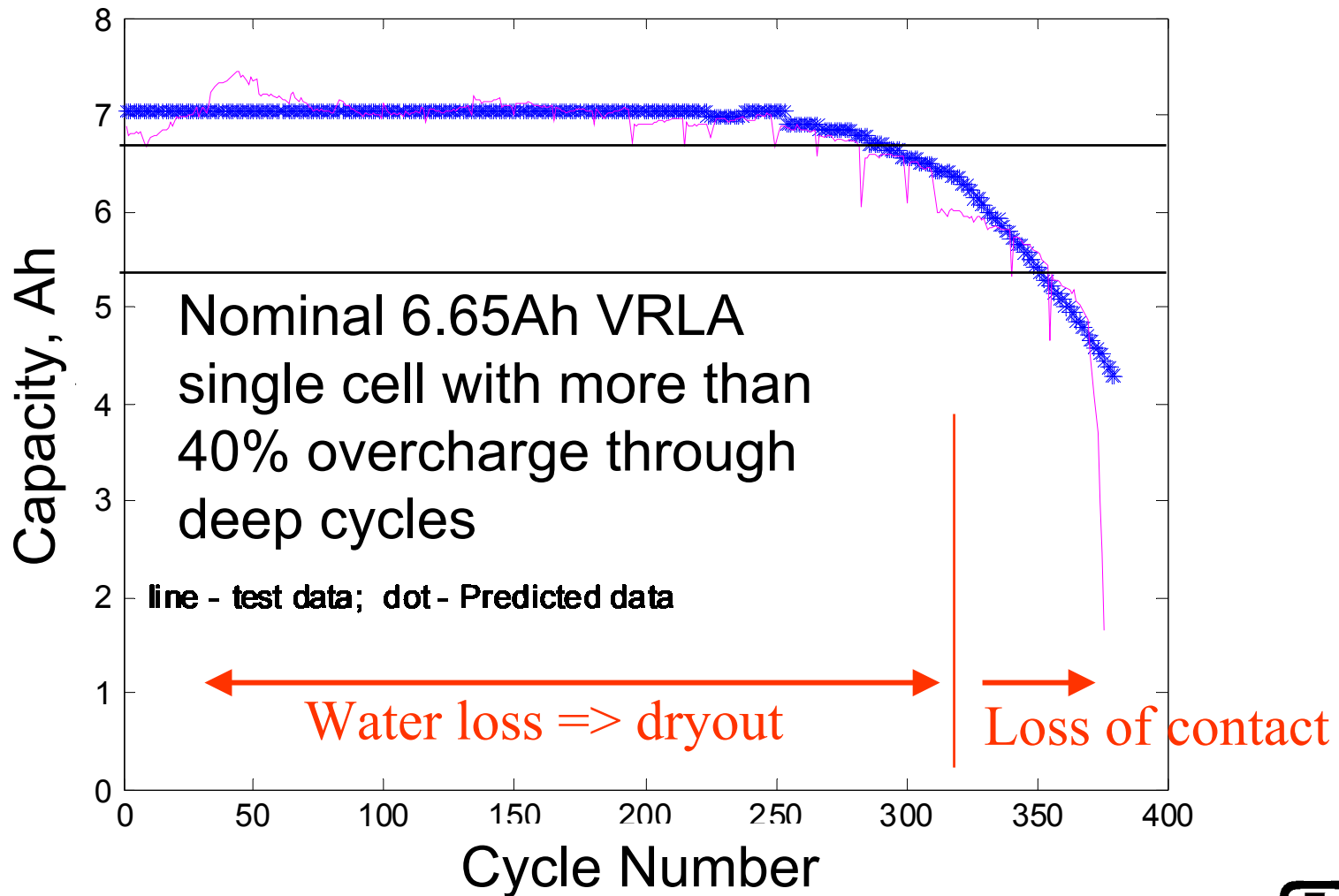
Cell Voltage versus SOC in Cycles

➔ Determining Available Capacity through Cycles

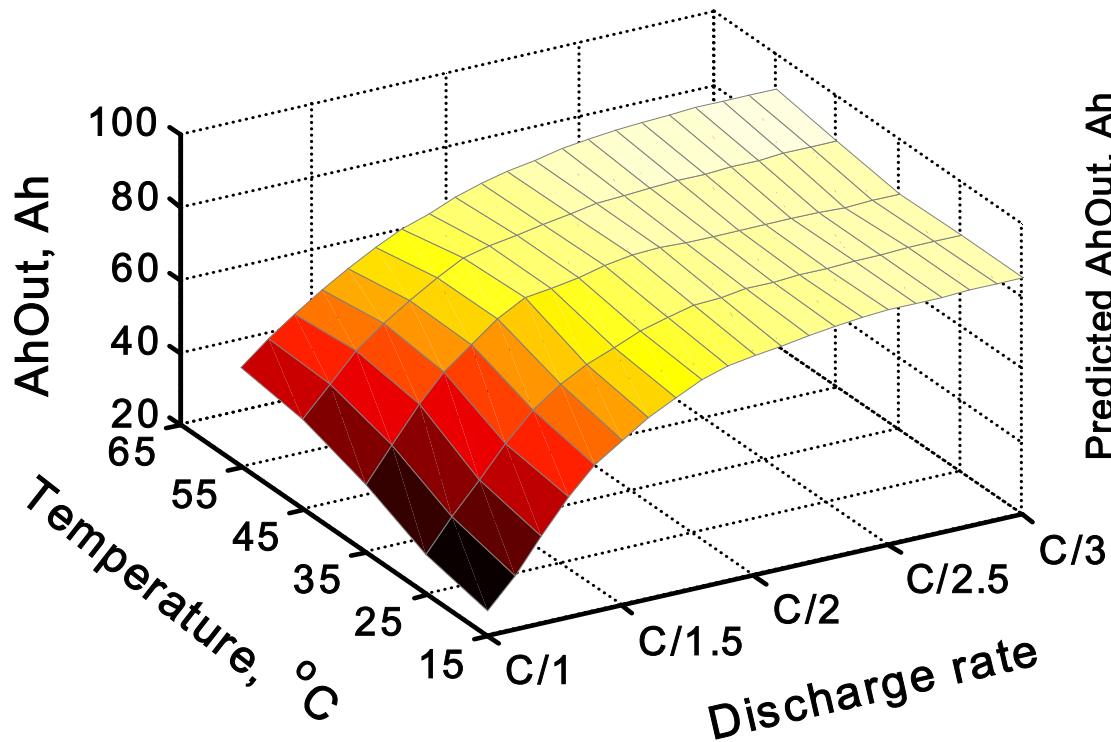


ECM Prediction:

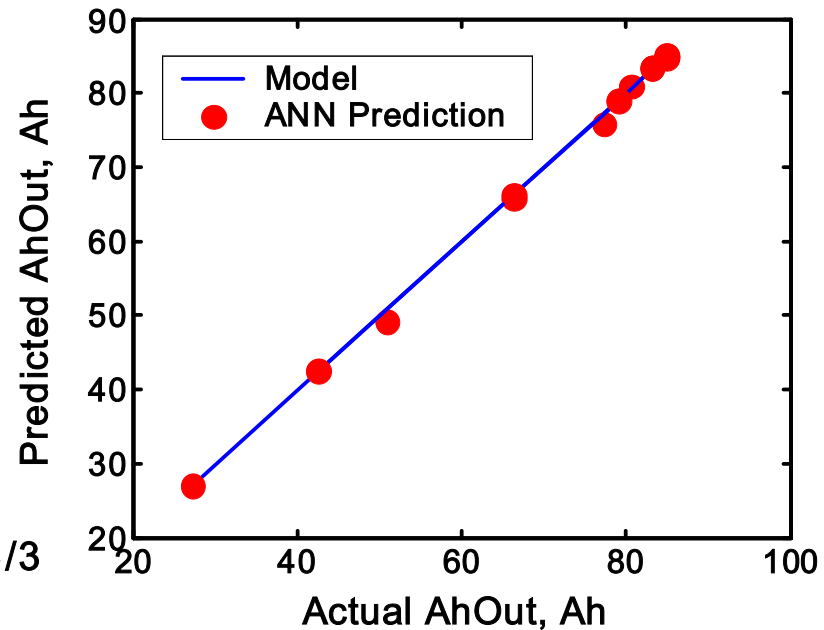
Cycle Life Predicted versus Measured



Artificial Neural Network: Capacity Discharge Modeling



ANN Model



Model Error



Summary

- ❑ A simple equivalent circuit model can be used to describe VRLA performance.
- ❑ Including two degradation processes (i.e., dryout and grid corrosion) in the model, we can predict life under duty cycles.
- ❑ Temperature dependence of battery performance can be modeled. Thermal impact on life needs to be addressed.
- ❑ Preliminary predictive data can be generated for artificial neural networks (ANN) interpretation of battery life.
- ❑ ANNs were used to study the capacity loss of a lead acid battery as a function of temperature and discharge rate.
- ❑ This approach seems to enable the integration of ECM and ANN into an effective and practical tool for VRLA battery life prediction in stationary applications.



Future Work & Work in Progress

- ❑ Use limited cycle performance data to validate simple equivalent circuit model predictions.
- ❑ Collect relevant data for float charge conditions to facilitate model development and modification.
- ❑ Integrate equivalent circuit model with ANN for adaptive parameter correlation and training to develop an ANN model for life prediction.
- ❑ Future ANN work will consider:
 - ❖ Exploring the relationship of capacity loss with respect to temperature, time, charge/discharge rate and other critical parameters
 - ❖ Conducting Principal Component Analysis to identify critical parameters for degradation during standby and duty cycle periods.



Acknowledgements

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- ☐ **Point of Contact: Rudy Jungst, Long-Life Power Sources, Sandia National Lab.**